HIGH-PERFORMANCE TARGET TRACKING USING TRACKER FUSION IN A TRACK-WHILE-SCAN RADAR

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ABSTRACT

The main problem that appears with tracking high-performance targets is the severe random change in the target motion in the model used by a uni-modal filter; e.g., Kalman filter. The interacting multiple model (IMM) can be considered as a multi-modal approach that solves Kalman filter problems with nonlinear target models. Though, it still requires prior knowledge about the target model as well as limited to white Gaussian noise. An adaptive filter that is able to deal with nonlinear models as well as colored noise is the particle filter. The efficiency and accuracy of the particle filter and its extensions depend mainly on two key factors: the propagation function used to re-allocate the particles and the number of particles used to estimate the posterior distribution. High performance targets with maneuverability that exceeds 7g need more particles to be tracked successfully. On the other hand, more particles mean more complexities in the tracking algorithm. In this paper, high-performance targets are tracked by fuzzy logic particle filter (FLPF); which uses fuzzy logic systems (FLS), to track targets when they start to maneuver. It estimates the angular turn rate, which is included as a state component, and tunes dynamically the number of particles used to estimate the posterior distribution. Meanwhile, when the target is moving according to a linear model, the unscented Kalman filter is used to track it. A tracker fusion technique is proposed to reduce the computation load when the target is non-maneuvering by using the unscented Kalman filter (UKF) as it has less computational load compared to the particle filters. The UKF is known to be optimal and is employed for state estimation for linear and Gaussian systems. The proposed technique performed well when tracking a high-performance target up to a maneuver equals to 13g using the model of a T-38 Talon training aircraft. Moreover, as for the computation load, it has been decreased due to the use of UKF when the target is moving according to a linear model.

I. INTRODUCTION

Target tracking is a hybrid estimation problem in which we predict the future trajectory of an object based on its previous states. A target such as a military aircraft may thrust, roll, and pitch; which results in a nonlinear model due to aircraft control and turbulence. The extended Kalman filter (EKF) and its higher orders are methods to solve such a problem. In the EKF, the real nonlinear models and non-Gaussian errors are approximated to linear and Gaussian in the neighborhood of the track [1,2]. An alternative to the EKF is to use the unscented Kalman filter (UKF) which was introduced in to offer superior performance to that of the EKF [3].

The UKF is optimal and is employed for state estimation for linear and Gaussian systems. The innovations from the UKF are used as test statistics, based on which hypothetical tests are carried out for maneuver detection. In target tracking, however, the actual measurement system is typically nonlinear and noise may exhibit non-Gaussian behavior. A strategy for estimating the target state in such a situation is to use the fuzzy logic particle filter (FLPF) [4].

The use of multiple trackers has many advantages over the system such as increased system reliability, robustness, and survivability. The main objective of tracker fusion is to reduce computation load. When the target is non-maneuvering, UKF tracker is used instead of the FLPF as the UKF has less computational load compared to the FLPF [5]. The UKF and FLPF are implemented

at a Track-While-Scan (TWS) radar system to track the target. At each scan period, both trackers transmit binary data regarding a potential maneuver to the fusion center, where decision fusion is performed to detect the potential occurrence of the target maneuver. This problem setting brings new challenges. The problem of correlation between state estimates arises when several trackers carry out dynamic system monitoring and each tracker has its own data processing system. While the observation noise of each tracker can be safely assumed to be independent, the process noise is the same in the dynamic model. This assumption makes different state estimates correlated. However, in classical distributed detection when optimal decision rules are required, the input observations are generally assumed to be independent and identically distributed under each hypothesis. In dynamic systems, the situation is much more complicated. The distribution of observations under each hypothesis is not readily available, but evolves as the dynamics proceed. Except for linear Gaussian systems, the correlation between observations in a general dynamic system is difficult to characterize.

This paper is organized as follows. Formulating the problem is given in Section 2. A tracker fusion using a hysteresis loop is explained in Section 3. In Section 4, maneuvering target models are mentioned. The TWS radar using tracker fusion technique is explained in Section 5 followed by performance analysis and experimental results. Finally, a conclusion is given.

II. PROBLEM FORMULATION

Let us assume the non-maneuvering target hypothesis to be H_0 and the maneuvering target hypothesis to be H_1 defined as follows:

$$H_0 : \boldsymbol{x}_{k+1} = F_k^0 \boldsymbol{x}_k + \boldsymbol{v}_k \tag{1}$$

$$H_1 : \boldsymbol{x}_{k+1} = F_k^1 \boldsymbol{x}_k + \boldsymbol{v}_k \tag{2}$$

where F_k^l is the state transition matrix and $\boldsymbol{v}_k^l$ is the process noise under the hypothesis l at scan period k. Parallel distributed maneuver detection is shown in Figure 1.

In this block diagram, the target behavior is governed by the hypothesis H_0. At each scan period k, the tracker detects a jump from the normal model to a maneuver model based on its own observations as follows:

$$d(u_k) \underset{<_{\delta_k=0}}{\overset{\geq^{\delta_k=1}}{}} \xi \tag{3}$$

where $d(.)$ is the fusion center decision statistic, u_k is the error between the target's predicted and actual position, ξ is the corresponding threshold, and δ_k is the global decision at scan period k. The global decision is fed back to the trackers so they can either update the state distribution based on their own observations (when δ_k=0) or announce the occurrence of target maneuver (when δ_k=1). In case of non-maneuvering target, the UKF is used. Otherwise, the FLPF is used in a case of maneuvering target.

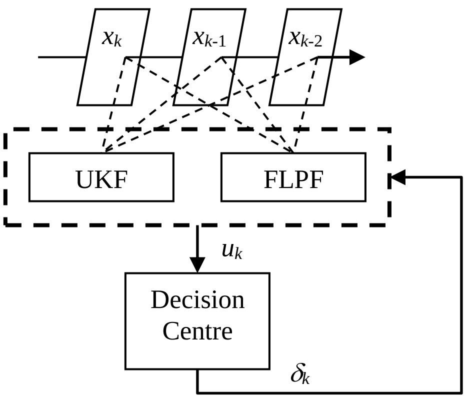

Figure 1. Maneuver detection block diagram.

Therefore, the tracker fusion can be explained as follows. Assume a target was detected for the first time at scan period k-1. The target's behavior would be governed by hypothesis H_0; i.e. non-maneuvering target. Consequently, the predicted target's state at scan k would be calculated through the UKF tracker. Comparing the target's actual state to the predicted one at scan k, the error u_k would be extracted. Comparing u_k to the appropriate threshold corresponding to the antenna scan rate of the TWS radar, the target can be distinguished as maneuvering or not. If u_k exceeds the threshold ξ, the target is considered maneuvering and the algorithm would switch to the FLPF tracker. Otherwise, the UKF would continue tracking the target.

III. TRACKER FUSION USING HYSTRESIS LOOP

However, using one threshold ξ may increase the computation load if the error varies in the neighborhood of the threshold. The MTT algorithm would switch from UKF to FLPF every time the error surpasses the threshold and vice versa. Therefore, a hysteresis loop is proposed as shown in Figure 2. If the target is moving in a straight line or slowly maneuvering, the UKF would be used. If the error u_k exceeds a certain threshold ξ_2, the target would be considered maneuvering and the algorithm would switch to FLPF. The FLPF would track the target until the error goes below a threshold $\xi_1 < \xi_2$. Obviously, the target would be either moving in a straight line or slowly maneuvering and the UKF is activated.

Therefore, if the error u_k is between ξ_1 and ξ_2, the hypothesis used in the scan period k would remain as it was in the scan period k-1. If the error u_k exceeds the threshold ξ_2, the system would be forced to follow hypothesis H_1. Meanwhile if the error goes below the threshold ξ_1, the system would be forced to follow the hypothesis H_0.

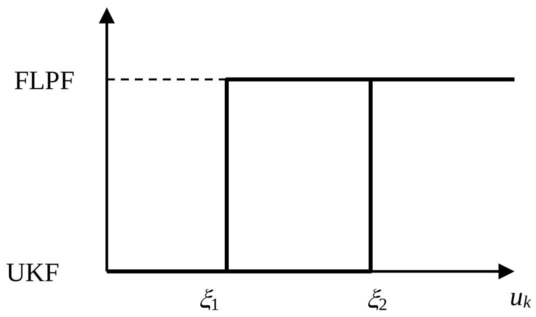

Figure 2. Tracker fusion using hysteresis loop.

To track multiple targets, the merged probabilistic data association (MPDA) approach [6] is used together with the UKF tracker. Meanwhile, assuming the observations are mutually independent on a scan-to-scan basis, the independent-sample based joint probabilistic data association (ISBJPDA) approach [7] is used together with the FLPF tracker.

IV. MANEUVERING TARGET MODEL

Maneuvers may be defined as a series of changes in direction and position for a specified purpose (as in changing course, switching tracks, or docking). Almost all maneuvering target tracking methods can be represented by some known mathematical models sufficiently accurately. The most commonly used such models are those known as state-space models, in form stated in Equation (4) with additive noise,

$$x_{k+1} = F_k(x_k) + v_k \tag{4}$$

$$z_k = H_k x_k + \omega_k \tag{5}$$

One of the major challenges for target tracking arises from the target motion uncertainty. This uncertainty refers to the fact that an accurate dynamic model of the target being tracked is not available to the tracker.

Target motion models are normally classified into two classes: maneuvering and non-maneuvering motion models. A non-maneuvering motion is the straight motion at a constant velocity, sometimes also referred to as the uniform motion. All other motions belong to the maneuvering mode.
Such motion is preferably specified in terms of the turn rate $\dot{\varphi}$. In the CT model with unknown turn rate, the turn rate is included as a state component, to be estimated. The FLPF is used to estimate the angular turn rate $\dot{\varphi}_k$ of the target. Consequently, the value of $\dot{\varphi}_k$ replaces $\dot{\varphi}$ in the transition matrix F_k. where:

$$x_{k+1} = F_k\left(x_k\right) + \nu_k$$
$$= \begin{bmatrix} 1 & 0 & \frac{\sin\dot{\varphi}T}{\dot{\varphi}} & -\frac{1-\cos\dot{\varphi}T}{\dot{\varphi}} \\ 0 & 1 & \frac{1-\cos\dot{\varphi}T}{\dot{\varphi}} & \frac{\sin\dot{\varphi}T}{\dot{\varphi}} \\ 0 & 0 & \cos\dot{\varphi}T & -\sin\dot{\varphi}T \\ 0 & 0 & \sin\dot{\varphi}T & \cos\dot{\varphi}T \end{bmatrix}\left(x_k\right) + \nu_k \tag{6}$$

V. TWS RADAR USING TRACKER FUSION

Figure 3 shows the architecture of the proposed TWS radar using the tracker fusion technique explained previously. At scan period *k*, the targets' states are fed to both MPDA and ISBJPDA as well as the error calculation block. The actual targets' states ($\boldsymbol{x}_k$) are assigned each to its corresponding track through the MPDA and ISBJPDA. Knowing the antenna scan rate, each target's state is compared to the predicted position calculated at the previous scan. In addition, the error calculation block generates the errors u_k^0 and u_k^1. Both errors are fed to the decision center to compare the error with the threshold ξ_k.
Based on the decision rule mentioned in Equation (3), a decision δ_k is taken whether the target of interest is maneuvering or not. The decision is fed to both trackers to decide which one should be used. If the target is a non-maneuvering target, the UKF tracker is used; otherwise, the FLPF is used.

VI. PERFORMANCE ANALYSIS

5.1 Experiment Setup

To simulate the backscattered signals from different aerial targets, the program package "*Radar Target Backscattering Simulation*" (RTBS) software [8] is used. The software package contains two programs: Target_editor.exe and BSS.exe. Different target models can be created or edited in Target_editor.exe. Meanwhile, the output of an amplitude or phase detector placed at the end of a linear receiver channel is calculated in the BSS.exe. The results of backscattered signals are saved in a data file that is processed by the main tracking program written in MATLAB 7.0. 500-Monte Carlo runs were used to get the experimental results. The probability of detection (P_d) is set to be 0.9 and probability of false alarm (P_{fa}) is 10^{-4}.

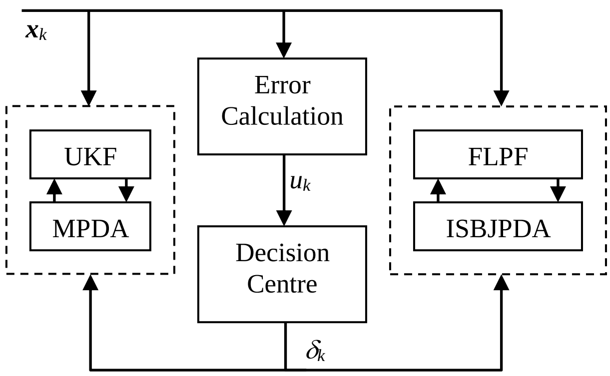

Figure 3. TWS radar with tracker fusion.

1.1.1 Radar system

A 2D coastal radar system is chosen for the experiment. The radar *pulse repetition frequency* (PRF), f_r, is assumed to be 1100 Hz. The antenna pattern has a "Cosine" amplitude distribution to provide low Side-Lobe Level (SLL). The transmitted pulse is a rectangular chirp frequency modulated to provide frequency agility against the foe's ECM. The pulse bandwidth is 200 MHz; meanwhile its width is 6 μs. The antenna aperture is 6 m and its scan period is chosen to be 5s (12 rpm). Finally, the electromagnetic field is polarized vertically to omit backscattered pulses from sea waves. Also, the noise measurement is set to 50 m and the clutter density set to 0.02.

1.1.2 Target model

A T-38 Talon trainer aircraft doing an acrobatic trajectory is considered because it may reach a 13g maneuver as it is not loaded with fuel or armaments. The T-38 Talon is a twin-engine, high-altitude, supersonic jet trainer used in a variety of roles because of its design, economy of operations, ease of maintenance, high performance and exceptional safety record. It is used primarily by Air Education and Training Command for undergraduate pilot and pilot instructor training. Student pilots fly the T-38 to learn supersonic techniques, aerobatics, formation, night and instrument flying and cross-country navigation. Consequently, the T-38 has more maneuverability than other fighters especially because it is not armed, which means it weighs less. Air Education and Training Command uses the T-38 Talon to prepare pilots for fighter aircraft such as the F-15.

1.2. Experimental Results

The UKF is set to be the TWS radar system default tracker. In this experiment, the T-38 Talon is performed a 13g acrobatic trajectory. It was moving on a straight-line trajectory before starting to maneuver. The RMSE between the true and estimated position is shown in Figure 4 where the periods when the FLPF is active can be distinguished by shaded rectangles. When the T-38 starts to maneuver, the RMSE increases to 79m, approximately. When the RMSE surpasses the threshold ξ_2, the FLPF is activated and starts to track the maneuvering target. Consequently, the RMSE converges to its steady state and goes below the threshold ξ_1. Thus, the UKF is activated and starts to track the target when it is moving in a straight line till the next maneuver.

Figure 5 shows the true and estimated trajectories. It can be shown clearly that the predicted trajectory is almost the same as the actual one. It may only deviates when the target starts to maneuver because the tracker is still using the UKF. When the tracker fusion switches to the FLPF, the predicted trajectory starts to follow the actual one. In this paper, the tracker fusion thresholds, ξ_1 and ξ_2, are predefined to be 3 m and 62 m, respectively. These values have been chosen according to Monte Carlo simulation. The value of ξ_1 (3 m) was chosen to equalize the steady state error value when using the UKF to track the target following a linear model. Meanwhile, the value of ξ_2 (62 m) was chosen to equal the maximum error value before the UKF starts to lose the target.

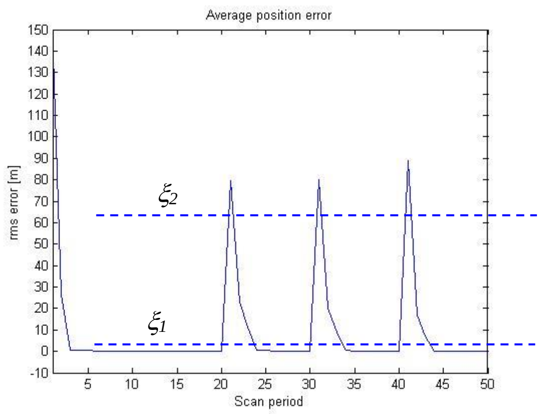

Figure 4. RMSE between predicted and estimated position of the T-38 Talon using the tracker fusion technique.

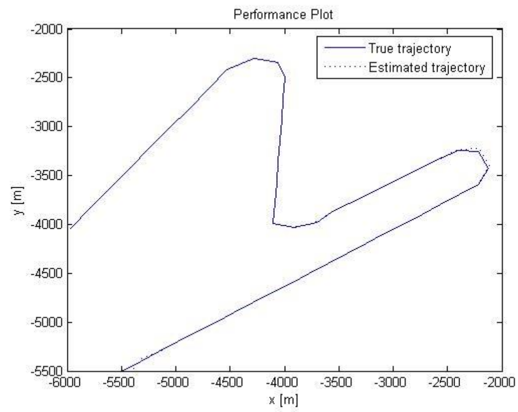

Figure 5. True and estimated trajectory of the T-38 using tracker fusion technique

VII. CONCLUSION

The tracker fusion is used to switch between UKF and FLPF according to the maneuverability of the target, which is measured by the FLS. The UKF has been used to track non-maneuvering and low-speed maneuvering targets since it shows an acceptable performance. The main advantage of the UKF is that it has a lighter computation load compared to the IMM and the proposed FLPF. The UKF has been chosen as the default tracker in the proposed TWS radar with tracker fusion. If a target starts to maneuver, the error between the predicted and measured target's state will increase. When the error surpasses a certain threshold, a decision centre activates the FLPF which starts to track the maneuvering target. Switching between trackers may increase the error compared to the RMSE if the target were tracked by FLPF only. However, even when a target is performing a 13g maneuver, it can still be tracked successfully with less computation load since the UKF is used to track non-maneuvering and low-speed maneuvering targets.

VIII. FUTURE WORK

The proposed algorithm was designed and implemented using MATLAB because it is compatible with other languages and software; e.g., Visual C++ and LabVIEW. To obtain a completely integrated TWS radar system in the future, the proposed algorithm could be implemented using a high-level programming language.

Also, the problem of tracking multiple targets in the space using a 3D radar system should be considered to track maneuvering targets when they roll, pitch, and/or yaw.

In addition, the algorithm processing time could be calculated accurately to evaluate the performance for its applicability to real-time tracking. In all of our experiments, radar parameters, targets' models, noise, and clutter were simulated to evaluate the performance of the proposed FLPF algorithm and MPDA approach. To better evaluate the system, real radar and data would be needed.

Moreover, the thresholds ξ_1 and ξ_2 values should be investigated to be adaptive according to the target's maneuverability as it was set to constant values in the previous experiment.

In terms of implementation it would be interesting to implement the algorithm on an embedded system. The requirements for implementing the algorithm in a commercial embedded system can be investigated in the future, and we suggest this for a future project.

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BIOGRAPHY

Hazem Kamel was born in 1970, Cairo – Egypt. He was graduated from the Military Technical College, Egypt in 1993 with grade "Excellent with Honors". He was rewarded the "Medal of Duty" by the Egyptian President. He worked as a teacher assistant and research assistant in the Military Technical College in the period from 1994 to 2003. He received the M.Sc. degree in electrical engineering in 1999. Hazem Kamel studied his Ph.D. in the University of Calgary and was graduated in 2007. His fields of interest are radar engineering, multiple target tracking, adaptive filters with real-time applications. He is a in the Egyptian engineering syndicate. He helped in the development of many undergraduate and postgraduate courses in the Military Technical College. As well, he took part in many researches in radar engineering. Nowadays, he is the head of radar engineering department in the Military Technical College, Egypt.

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